NON-INVASIVE SMART PESTICIDE RESIDUE ANALYZER FOR FOOD SAFETY

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Introduction:

Pesticides are extensively used in the cultivation of fruits and vegetables to protect crops from pests. However, residues of these chemicals can persist on produce even after washing, posing significant food safety risks. The Food and Agriculture Organization (FAO) and the World Health Organization (WHO) have confirmed widespread pesticide contamination in some regions, with up to 30% of food samples exceeding permissible chemical limits. Short-term exposure can cause vomiting and skin rashes, while long-term exposure may disrupt hormonal and reproductive systems and increase cancer risk. Children and pregnant women are especially vulnerable.

Conventional pesticide detection relies on laboratory-grade instruments such as gas chromatography (GC) and liquid chromatography-mass spectrometry (LC-MS). While highly accurate, these methods are expensive, time-consuming (testing can range from one hour to several days), require trained personnel, and cannot be used for on-site or real-time field testing. These limitations make them unsuitable for farmers, small retailers, and everyday consumers.

The Non-Invasive Smart Pesticide Residue Analyzer is a compact, field-deployable device that uses dual-wavelength optical sensing (UV and IR), an STM32 microcontroller, IoT connectivity, and a Tiny Machine Learning (TinyML) MLP neural network to detect and classify pesticide residues in real time. An automated post-detection chamber cleaning mechanism is also integrated, elevating the device from a passive analyzer to an active food safety tool.

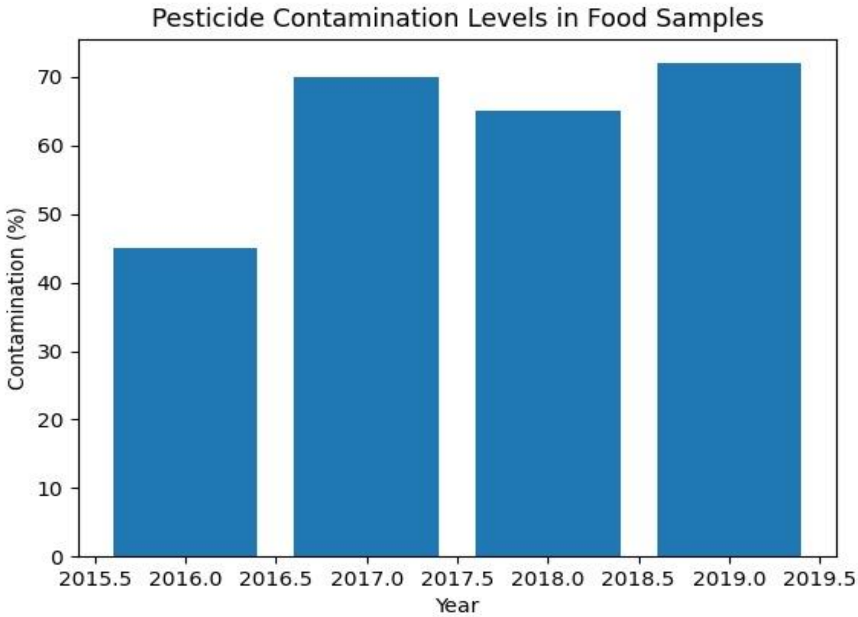

Figure 1: Year-wise Pesticide Contamination in Food Samples

Objectives:

1. Design a non-invasive sensing system capable of detecting pesticide residues on food surfaces without degrading the nutrients of the food.
2. To design and implement an IoT dashboard for real-time visualization of pesticide residue data.
3. Design and train a Machine Learning model that detects and classifies different pesticide residues from spectral data.
4. To develop a system to remove pesticide residues from food items after detection.

Methodology:

A. System Architecture

The proposed pesticide detection system is a compact, IoT-enabled solution based on a four-stage architecture: sensing, processing, cleaning, and communication. The process begins in a light-shielded chamber where UV and IR light illuminate the sample, and photodiodes capture the reflected spectral data, which is analyzed by STM32 and ESP32 microcontrollers to identify pesticide signatures. The results are transmitted in real time via Wi-Fi to a cloud-based dashboard for remote monitoring. Upon detection of contamination, an automated cleaning mechanism is triggered, employing mist generation with a baking soda solution, followed by water spraying and controlled airflow drying to remove residues. A mandatory re-detection step is then performed to verify complete decontamination, forming a closed-loop system that ensures reliability and repeatability.

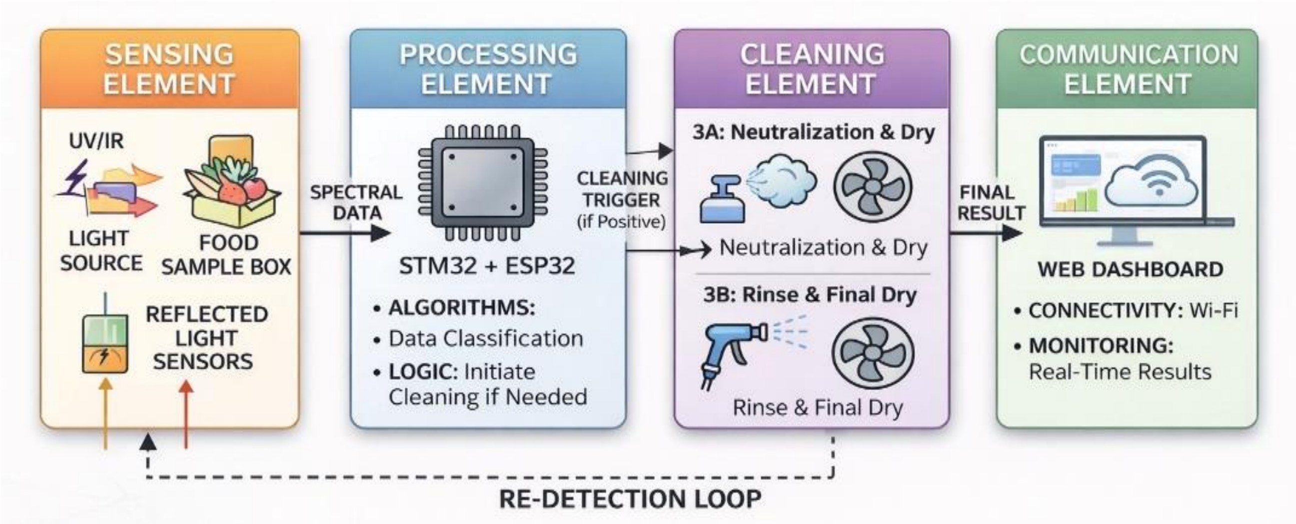

Figure 2: System Architecture

B. Hardware Architecture

The sensing subsystem employs a 365 nm UV LED and a 940 nm IR LED as controlled illumination sources. Reflected light is captured by two photodiodes, the GUVA-S12SD (UV-sensitive) and the BPW41N (IR-sensitive), which convert reflected light intensity into analog voltage signals. These signals are fed to the STM32F411CEU6's 12-bit ADC channels. An ESP32 Wi-Fi module handles data relay to the cloud dashboard. The system is powered by a regulated DC supply, ensuring stable sensor operation.

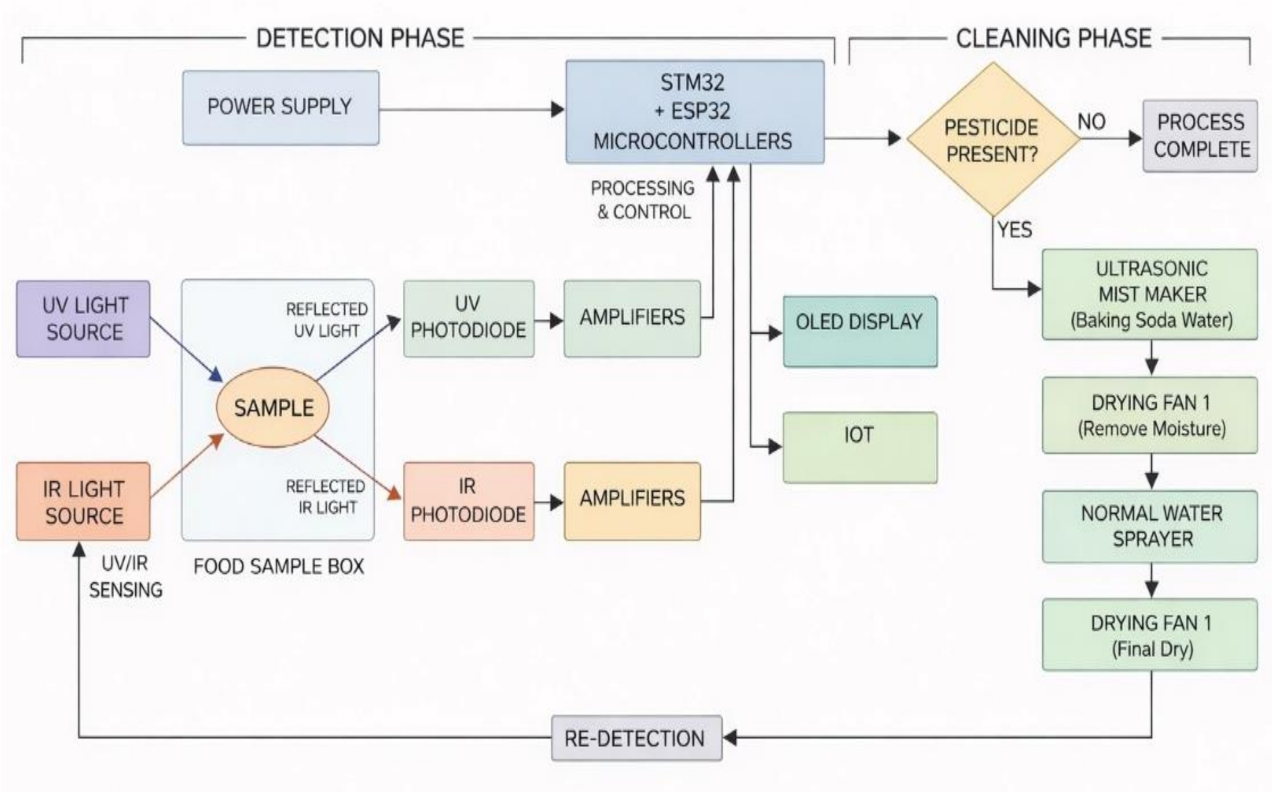

Figure 3: Block Diagram of the proposed model

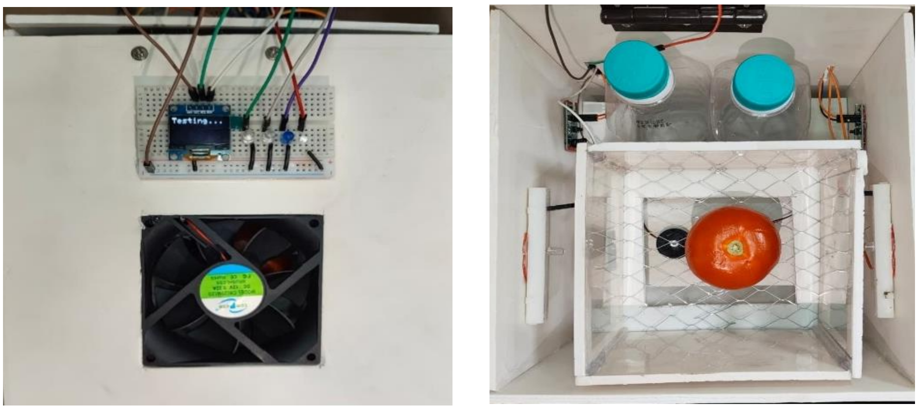

Figure 4: Hardware prototype showing display unit (top) and sensing chamber (inside)

C. Optical Sensing Principle

The device exploits the unique spectral interaction of different pesticide molecules with light. When illuminated by UV and IR sources, pesticide residues on fruit/vegetable surfaces alter the reflected light intensity in predictable, compound-specific ways. UV absorption is the dominant signature of Emamectin Benzoate; IR reflectance variation is the dominant signature of Lambda-Cyhalothrin. The dual-wavelength approach enhances selectivity compared to single-wavelength systems.

D. Signal Processing and Data Analysis

Analog voltage outputs from the GUVA-S12SD and BPW41N photodiodes are digitized by the STM32's ADC. The microcontroller applies experimentally established threshold values: a significant drop in UV photodiode voltage indicates UV-absorbing pesticide contamination, while variation in IR photodiode output indicates IR-affecting compounds. The system classifies samples into three categories: Clean, UV-Sensitive Residue (EBD), or IR-Sensitive Residue (LBC), enabling rapid, reagent-free decisions.

E. Machine Learning for Classification (TinyML)

To achieve robust classification beyond voltage thresholding, a Tiny Machine Learning (TinyML) pipeline is integrated. A dataset comprising UV, IR, and white-light sensor readings from clean and contaminated samples is collected. Key features, including individual signal intensities, temporal variations, and UV-to-IR ratios, are extracted and normalized to a 0–1 scale. A compact Multi-Layer Perceptron (MLP) is trained on these feature vectors to identify non-linear patterns associated with specific pesticide classes. The trained model is quantized to an 8-bit integer (int8) format and converted to TensorFlow Lite Micro format for deployment. During operation, the ESP32 executes edge inference in real time, outputting predicted pesticide class to the system dashboard.

F. IoT-Based Data Transmission and Monitoring

The ESP32 Wi-Fi module relays processed sensor data and classification results to an IoT cloud platform in real time. The cloud dashboard displays live UV and IR sensor voltage levels, pesticide detection status, and visual alerts upon contamination detection. Farmers, retailers, and food safety inspectors can remotely monitor food safety status via web or mobile interfaces, removing the need for laboratory equipment at the point of use.

G. Automated Post-Detection Cleaning Mechanism

A deterministic 40-second time-sequenced cleaning cycle is executed after each measurement to ensure chamber cleanliness and result repeatability. The STM32 controls the sequence upon receiving a trigger from the ESP32, validated with a 50 ms debounce to prevent false starts:

Table 1: Automated Cleaning Sequence Phases

Phase	Duration	Action
Initial Mist	0–10 s	Primary mist generator activated; fine droplets loosen residues.
Airflow Distribution	10–15 s	5V fan circulates mist uniformly for even coverage.
Secondary Injection	15–20 s	Secondary mist generator targets remaining stubborn residues.
Partial Drying	20–30 s	Primary mist off; secondary mist + 5V fan begins drying.
Final Evacuation	30–40 s	All mist off; 12V high-speed fan expels remaining moisture.

Result and Conclusion:

I. Pesticide Residue Detection

Experimental testing showed a clear voltage difference between clean and contaminated samples. The UV signal exhibited a reduction of approximately 19.08%[$(\mathbf{2.62}–\mathbf{2.12})/\mathbf{2.62} \times \mathbf{100}$], indicating strong absorption by pesticide residues, while IR variations further supported contamination detection. Clean samples produced stable high readings (“FOOD CLEAN”), whereas contaminated samples showed reduced values due to light absorption and scattering.

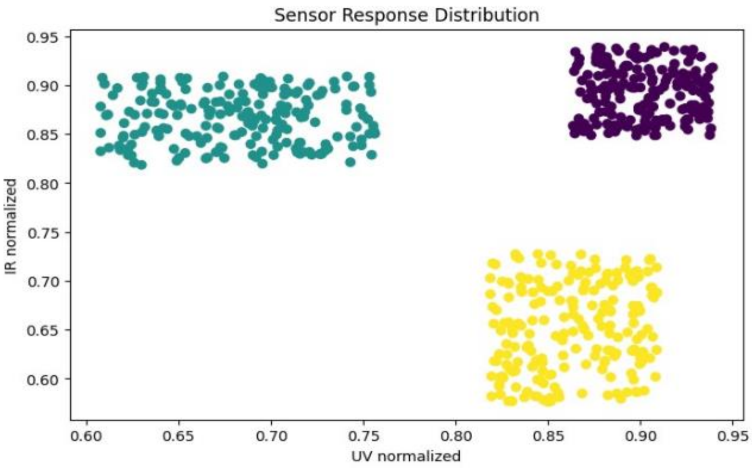

Figure 5: Sensor Response Distribution

The Sensor Response Distribution confirms distinct clustering of UV and IR data, demonstrating effective separation between clean and contaminated samples. This validates that dual-wavelength sensing provides reliable feature discrimination, which is further enhanced by machine learning.

The system successfully identifies pesticide types based on spectral characteristics:

- Emamectin Benzoate (EBD): Strong UV absorption (365 nm)
- Lambda-Cyhalothrin (LBC): Significant IR variation (940 nm)

II. Machine Learning Model Performance

The TinyML-based classification model achieved high performance with ~95–100% accuracy and zero misclassifications during testing.

- The learning curve shows rapid convergence with minimal overfitting
- The loss curve reduces smoothly to near zero
- The confusion matrix shows perfect diagonal classification

These results confirm that the model effectively captures non-linear relationships in sensor data and ensures reliable classification.

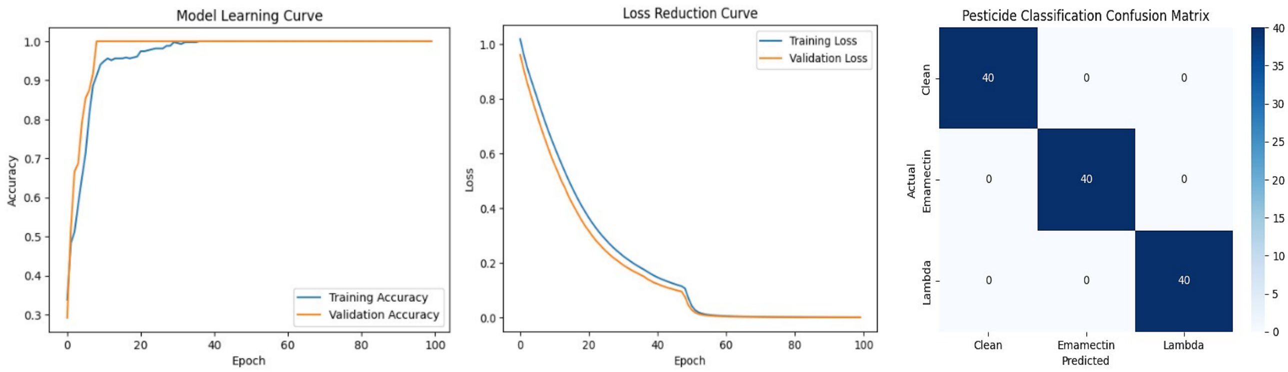

Figure 6: Graphs showing the Learning, Loss Reduction Curves, and Confusion Matrix

III. IoT Dashboard and Real-Time Monitoring

The IoT dashboard provides real-time visualization of UV and IR sensor values using an ESP32-based communication system. It enables instant alerts (e.g., “FOOD CLEAN” or pesticide detected) and simplifies data interpretation through a user-friendly interface.

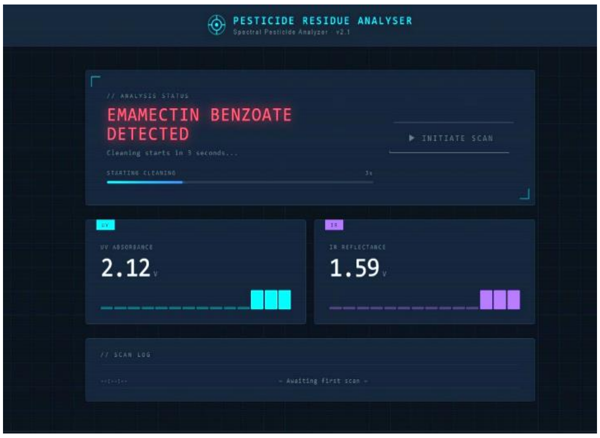

Figure 7: Pesticide Detected

Figure 8: Food Clean

IV. Automated Cleaning Mechanism

The system incorporates a deterministic 40-second cleaning cycle using mist generation and airflow. This process removes residual contaminants, maintains chamber hygiene, and ensures repeatable measurements across multiple test cycles.

Figure 9: Cleaning in Progress

V. Comparative Analysis

Compared to conventional laboratory methods, the proposed system:

- Reduces testing time significantly
- Eliminates chemical reagents
- Provides ~90%+ accuracy
- Enables portable, non-destructive, field-level testing

This makes it suitable for farmers, retailers, and food inspectors.

Conclusion

1. The developed system demonstrates a compact, non-invasive, and cost-effective solution for real-time pesticide detection. By integrating dual-wavelength sensing, embedded processing, TinyML, and IoT, it achieves high accuracy while eliminating the limitations of laboratory-based techniques.
2. The system is particularly beneficial for field deployment, enabling rapid food safety assessment without specialized infrastructure. Its scalability and affordability make it suitable for widespread adoption, especially in regions with limited laboratory access.
3. Future improvements include multispectral sensing, enhanced ML models with diverse datasets, and device miniaturization for consumer-level use, along with mobile integration and cloud-based analytics.

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Future Scope:

The future scope of this project includes:

1. Multispectral and Hyperspectral Sensing: Integrate additional wavelength bands to extend detection to a broader range of pesticide compounds.
2. Enhanced ML Models: Train larger, more diverse datasets to improve classification accuracy and reduce false positives across varied crop types and environmental conditions.
3. Smartphone Integration: Develop a companion mobile application for real-time result display, historical data tracking, and contamination alerts for end-users.
4. Cloud Analytics: Extend the IoT platform to support large-scale agricultural supply chain monitoring with predictive contamination analytics.
5. Miniaturization: Design a palm-sized next-generation device for consumer-level adoption by farmers and food safety inspectors.